3D Imaging
and VLSI Applications

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3D Imaging

3D Imaging is inspiring research with results in interesting places:

A YouTube video entitled: “Head Tracking for Desktop VR Displays using the Wii Remote”, by Dr. Lee at Carnegie Mellon

http://www.youtube.com/watch?v=Jd3-eiid-Uw

3DTV European-funded:

http://www.3dtv-research.org/index.php

3D Consortium: Japan, Korea

http://www.3dc.gr.jp/english/index.html
3D Imaging

Research on every continent:

Universities (NYU, Carnegie-Mellon, Tampere, RIT)
Large Companies (Philips, Mitsubishi, TI, Samsung, Sanyo)
Entrepreneurial Companies (Newsight, TrueVision, SeeReal, VizBox)
Military, Government (Air Force, Army, Space Agencies)
Medical (GE Medical Systems, Aachen Hospital, Brigham and Women’s Hospital, Stanford Radiology)
Standards Bodies (MPEG, H.264, JPEG)
Why VLSI in 3D Imaging?

- In industry, VLSI is the key to the timing of new features and product introductions
  - My background with one foot in VLSI, one foot in Signal Processing and Systems, was very valuable to my career
- Why is the time ripe now for VLSI in 3D Imaging applications?
  - 3D imaging industry is near the “tipping point” for growth
  - New VLSI for 3D imaging is just emerging
  - The need for VLSI is there (to make real-time possible)
  - There are a broad range of opportunities to design new VLSI
3D – Fertile Fields of Study

- Image Capture Devices (Light to Electrons)
- Image Processing (Algorithmic VLSI)
- Image Display Devices (Processing, Interfacing, Electrons to Light)

Each has its own challenges and opportunities, and as the technologies are developed, the VLSI applications will be uncovered. In most areas, the computation time is a barrier when executing on standard computing platforms.
3D Image Capture

- **2D plus Depth Imagers:**
  - CMOS depth sensing using phase (Photonic Charge Pump) Nicola Massari in SPIE online 2006
  - IR, Radar, Sonar Illumination & Detection
  - Multiple Camera Data Fusion

- **Integral Photography**
  - Imagers with Microlens Arrays
    Manuel Martinez-Corral, in SPIE online 2006

- **Medical Radiology:**
  - 3D CMUTs (Capacitive Micromachined Ultrasonic Transducers) T. Khuri Yakub in SPIE online 2006
  - CT and MRI are 3D media
3D Image Display

- **Autostereoscopic**
  - Integral Photography
  - Lenticular Lens (multiple views)
    - Philips Display
  - Single user (head tracking)
- **Holographic**
- **Plasma in air**
3D Image Processing

- Compression, DCT
- Registration
- Compositing
- 3D from 2D (using shadow, light, multiple cameras, 2D plus depth, etc.)
- Segmentation - example follows:
Example: 3D Ultrasound Segmentation

- Key algorithms and architectures are required as technology evolves
- Presenting here the contributions from my PhD dissertation

Making the Link from Algorithm to VLSI:
- Some thoughts on VLSI for 3D Image Segmentation follow the algorithm discussion
Introduction to 3D Segmentation

- Segmentation is an ill-posed problem
  - For medical ultrasound imaging, most segmentation is done by hand
- In 3D good segmentation can allow rendering of an organ to improve diagnosis
  - clinicians look at 2D slices and 3D volumes
  - 3D imaging could also assist surgeons
- This algorithm will focus on 3D segmentation of ultrasound medical images
Ultrasound Breast Images

- Carcinoma (4x4x4mm) (Case A)

- Carcinoma (Case B)
Ultrasound Breast Images with Hand Segmentation

- Carcinoma (4x4x4mm)(CaseA)
- Carcinoma (CaseB)
Segmented Images
Standard Bayesian Techniques

2D EM/MAP-ICM, (CaseA)

2D EM/MAP-ICM (CaseB)
Segmented Images
Research Result

3D EM/MPM (CaseA)

3D EM/MPM (CaseB)
Segmented Images
Research Results Overlay

3D EM/MPM (CaseA)  3D EM/MPM (CaseB)
Algorithm Discussion – Deep Dive

- Bayesian Segmentation
- MPM optimization approach vs. standard approach
- Comparison using test images
Problem: Estimate X given Y

Maximum A Posteriori (MAP) estimation: (Bayesian)

\[ P(X|Y) = \frac{P(Y|X) \times P(X)}{P(Y)} \]

- Prior Distribution: \( p(X) \)
- Posterior Distribution: \( p(X | Y) \)

\[ \hat{x} = \arg \max_x p(X | Y) \]

\[ = \arg \max_x \log p(Y | X) + \log p(X) \]
Assumptions

- **Forward Probability** –
  - Gaussian Distribution
  - Independent, Identically Distributed

- **Prior Probability** –
  - Markov Random Field
  - Gibbs Distribution
Markov Random Fields and Markov Chains

- **Concept 1:** Pixel Neighborhood
  - $X_s$ = Pixel Under Consideration
  - $X_r$ = Neighborhood Pixels
  - $C$ = Clique, if symmetric system
  - Markov property

- **Concept 2:** Markov Chain & Optimization
  - Certain Markov Chains are Ergodic
  - Important for proof of Convergence
  - Gibbs Distributions, Simulated Annealing
MRF Model

- PMF of Prior on Class Labels: (Gibbs Distribution):

\[
p(x) = \frac{1}{Z} \exp \left\{ - \sum_{r \in C} \beta t(r, s) - \sum_{r \in C} \gamma_{x_r} \right\}
\]

\[
t(r, s) = \begin{cases} 
0; & x_r = x_s \\
1; & x_r \neq x_s
\end{cases}; \quad C = \text{Clique of X}
\]

- Clique defines Spatial Interaction, Markov Property
- Markov Random Field -> Convergence of Optimization
MRF Model

- The Posterior Distribution (using Bayes Theorem):

\[
p_{X|Y}(x | y, \theta) = \frac{f(y | x, \theta) p(x)}{f(y | \theta)}
\]

\[
= \frac{1}{Zf(y | \theta)} \prod_{s \in S} \left[ \frac{1}{\sqrt{2\pi \sigma_{x_s}^2}} \exp \left( - \frac{(y_s - \mu_{x_s})^2}{2\sigma_{x_s}^2} \right) - \sum_{\{r,s\} \in C} \beta t(x_r, x_s) - \sum_{r \in C} \gamma x_r \right]
\]

- Is a Likelihood function
- And a Gibbs Distribution
Maximizing

- MAP: Find Maximum of Posterior Distribution:

\[
\hat{x} = \arg \max_x p_{x|y}(x \mid y, \theta)
\]

\[
= \arg \max_x \prod_{s \in S} \left[ \frac{1}{\sqrt{2\pi\sigma_x^2}} \exp \left( -\frac{(y_s - \mu_{x_s})^2}{2\sigma_{x_s}^2} \right) \right] - \sum_{\{r,s\} \in C} \beta \ t(x_r, x_s) - \sum_{r \in C} \gamma_{x_r}
\]

\[
= \arg \max_x \mathbb{E}[x \mid y, \theta]
\]

- Clique and Markov Property makes product separable, operation on each term can be independent

- Gibbs Distribution property makes Gibbs Sampler form Markov Chain
Maximization of Posterior Marginals

Equivalent MAP Cost function:
\[ C(x, \hat{x}) = (1 - \delta(x_s - \hat{x}_s)) \]

MPM Cost function:
\[ C(x, \hat{x}) = \sum_{s \in S} (1 - \delta(x_s - \hat{x}_s)) \]

Minimize Expected Value of Cost
\[ \hat{x}_{MPM} = \arg\min_x E\{C(x, \hat{x}) \mid Y = y\} \]
\[ = \arg\min_x \sum_{x \in k} \sum_{s \in S} (1 - \delta(x - \hat{x}_s)) p_{X|Y}(x \mid y, \theta) \]
\[ = \arg\min_x \left\{ \left| S \right| - \sum_{s \in S} \sum_{x: x_s = \hat{x}_s} p_{X|Y}(x \mid y, \theta) \right\} \]
Minimize Expected Value of Cost (con’t)

\[
\hat{x}_{MPM} = \arg \max_x \left\{ \sum_{s \in S \{x:x_s = k\}} \sum_{y} p_X|Y(x \mid y, \theta) \right\}
\]

\[
= \arg \max_x \left\{ \frac{1}{P_{X_s|Y}(k \mid y, \theta)} \right\}
\]

This is the Maximizer of Posterior Marginals
MPM (why?)

- MAP-SA optimizes over large area (finds more global maximum)
  - Used when strong S/N
  - Can be locally misleading in poor S/N
- MAP-ICM is prone to finding local maxima
- MPM weights local choices
  - Can be better for poor S/N
  - May find edges more accurately
  - Poorer Consistency
    - For choices of Class across image
    - (May be advantage in ultrasound)
Research: Optimization Strategy

- Posterior Marginals MPM:
  \[
  \pi_{x_s} = \frac{1}{Z} \exp \{ x_s \mid x_r, y_s, \theta \}
  \]
  
  - Equal to posterior marginal distribution
  - Find distribution value for all choices of \( x_s \)
  - Compare \( \pi \) to a Uniform(0,1] random variable, choose change if greater
  - Forms Markov Chain
Gaussian Parameter Estimation

- How does one find \( \theta = \hat{\theta}_1, \sigma_1, \mu_2, \sigma_2, \ldots, \mu_N, \sigma_N \)?
- Use Expectation-Maximization algorithm to find these “hyper-parameters” Maximum Likelihood estimate.
- Nested loops:
  1. Initialize, random for \( \hat{x} \) and estimate for \( \theta \)
  2. Find segmentation \( \hat{x} \), by proposed iterative soln
  3. Find \( \theta = \hat{\theta}_1, \sigma_1, \mu_2, \sigma_2, \ldots, \mu_N, \sigma_N \) by EM
  4. Repeat 2, 3 until convergence
Estimation of Means and Variances

- Guesswork, Experience
- Introduce “Hyper” parameters
  - EM Algorithm
- EM and MPM together
  - MPM’s “time in state” scaled by:
    - Mean
    - Variance
  - Creates update for “Hyper” parameter
Comparison

- MAP-ICM and MAP-SA common techniques
- MPM has advantages for noisy images
  - Better localized solution
  - Better estimates for EM update parameters
- Complexity (average # of inner loops to convergence):
  - EM/MAP-ICM : 70
  - EM/MPM : 270
  - EM/MAP-SA : 500
- Apple test image:
  - Interior greyscale value = 33, exterior = 64
  - Initialization 4 classes: $\theta = (10,4.5,90,4.5,180,4.5,250,4.5)$
  - Gaussian noise added: $\sigma = (10,20,30,40,50,60,70,75)$
Apple optimization comparison

<table>
<thead>
<tr>
<th>Source</th>
<th>MPM</th>
<th>ICM</th>
<th>SA</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Source Apple" /></td>
<td><img src="image" alt="MPM Apple" /></td>
<td><img src="image" alt="ICM Apple" /></td>
<td><img src="image" alt="SA Apple" /></td>
</tr>
</tbody>
</table>

SNR = \( \infty \)
Summary of New Approaches

- Added automatic method to find optimal N (number of classes)
- Added automatic initialization method
- For ultrasound and other non-uniform attenuation images:
  - New model of mean of forward probability model
  - New probability “atlas” to compensate for attenuation
  - New combination of both with EM update equations
- Demonstrated best results with 3D EM/MPM as core
Gamma, Probability Variation

- Tumor and Background classes mixed in segmentation
  - Due to attenuation in ultrasound

- We use the Gamma from posterior distribution:

\[
p_{X|Y}(x \,| \, y, \theta) = \frac{f(y \,| \, x, \theta) p(x)}{f(y \,| \, \theta)}
\]

\[
= \frac{1}{Z_f(y \,| \, \theta)} \prod_{s \in S} \frac{1}{\sqrt{2\pi\sigma_{xs}^2}} \exp\left(-\frac{(y_s - \mu_{xs})^2}{2\sigma_{xs}^2}\right) - \sum_{\{r,s\} \in C} \beta t(x_r, x_s) \sum_{r \in C} \gamma_{x_r}
\]

- Linearly vary Gamma from top to bottom of image
  - In ultrasound, for the classes with lowest means
- Gamma can also be a probability “atlas” to drive the optimization
Automatic Gamma Selection

- Linearly vary Gamma from top to bottom of image
  - For lower class labels in ultrasound
- Tie to the forward probability model by the inverse of the Gaussian mean slope:

$$\gamma_k = A(-m^* s + B)$$

$s \in \{0, ..., 1\}$ (vertical dimension)
Results – 3D Comparison
ICM and MPM

Original Image
(175gs\A1PST1gs45)

3D EM/MAP-ICM
Segmented Image
7 ICM, Beta=3.2
4 classes

3D EM/MPM
Segmented Image
9 MPM, Beta=3.2
4 classes
Original vs Segmented 3D EM/MPM - Case A
Segmentation Algorithm: Conclusions

- Segmentation is best performed with EM/MPM for low SNR
- Using Gamma together with Variable Mean was shown to compensate for attenuation
  - Both in 2D and 3D results, in test and medical ultrasound images
  - Best when tied through inverse of the mean found in forward probability model
- Full 3D segmentation improves the volume rendering best
  - More coherent boundary
- Initialization is important
VLSI Applications to 3D Segmentation

- 3D processing requires large data sets
- Many 3D segmentation algorithms are iterative
  - Including 3D EM-MPM described here
- VLSI innovations will be required to realize real-time segmentation
  - Parallel computing, large data structure manipulation
- The application of VLSI to common 3D algorithms and to devices for 3D display and image capture is needed in several industries
Applying my Background

- My product success was frequently due to the correct planning of the VLSI design
  - How much should be in one chip?
  - What is the right Software to VLSI ratio?
- This requires a deep understanding of Moore’s law and current technology trends
- This also requires the algorithmic understanding of 3D image processing
Research Proposal

1. Research efficacy of algorithm for other modes of Medical Imaging and port algorithm to run with 3D slicer (Medical Imaging Visualization SW)
   - - this will be proposed for a new MURI

2. Design and test VLSI architectures (FPGA), demonstrate advantages of real-time segmentation

3. Build up a 3D Capture, Algorithm, and Display Laboratory – demonstrating the VLSI designs
Summary

● VLSI applications in 3D Imaging are required for industry growth

● The combination of Engineering and Radiology Departments at IUPUI provides the right applied research environment for these targeted VLSI applications in the field of 3D medical imaging

● VLSI applications to 3D Imaging opportunities will be the next target:
  ● Chip companies (Broadcom, ST, TI, IBM, …)
  ● Systems companies (Thomson, Philips, Matsushita, Samsung, Microsoft, DIRECTV, …)
Appendix – more Math
Optimization Strategies

Separating the MAP equation:

\[ \hat{x}_s = \arg \max_{x_s} \ p_{X|Y}(x_s \mid y, \theta) \]

\[ = \arg \max_{x_s} \left[ \frac{1}{\sqrt{2\pi \sigma^2}} \exp \left( - \frac{(y_s - \mu_{x_s})^2}{2\sigma^2} \right) - \sum_{\{r,s\} \in C} \beta_t(x_r, x_s) - \sum_{r \in C} \gamma_{x_r} \right] \]

\[ = \arg \max_{x_s} \left[ -\log \sqrt{2\pi \sigma^2} - \frac{(y_s - \mu_{x_s})^2}{2\sigma^2} \right] \]

\[ = \arg \max_{x_s} \ \{ x_s \mid x_r, y_s, \theta \} \]
Optimization Strategies - 1

- Descent Optimization, MAP - ICM:

\[
\hat{x}_s = \arg \max_{x_s} p_{X|Y}(x_s \mid y, \theta) = \arg \max_{x_s} \mathcal{U}(x_s \mid x_r, y_s, \theta) \\
= \arg \max_{x_s} \left[ -\log \sqrt{2\pi \sigma^2_{x_s}} - \left\{ \frac{(y_s - \mu_{x_s})^2}{2\sigma^2_{x_s}} \right\} - \sum_{\{r,s\} \in C} \beta_t(x_r, x_s) - \sum_{r \in C} y_{x_r} \right]
\]

- Find maximum
- Iterate over several visits to each pixel
- Direct Minimization – Iterated Conditional Modes (ICM)
Monte Carlo Markov Chain (MCMC) Strategy:

\[ \pi_{x_s} = \frac{1}{Z} \exp \left\{ \frac{1}{T} u[x_s \mid x_r, y_s, \theta] \right\} \]

- Find distribution value for all choices of \( x_s \)
- Compare \( \pi \) to a Uniform(0,1] random variable, choose change if greater
- Forms Markov Chain, Temperature is annealing schedule:

\[ T = \frac{3}{\log(1+t)} \]
EM: Estimate Hyper-Parameters
- Mixture distributions
- Soft-Decision in Overlap Region

Iterative 2-Step Process:
- Expectation Step:
  - For each of n-Classes: Theta = \( \hat{\theta} \) = Expected value of the means and variances
- Maximization Step:
  - One of three ways of solving:
    \[
    \hat{x}_s = \arg\max_{x_s} \theta(x_s | x_r, y_s, \theta)
    \]
Expectation Step:
- ML estimate for Theta, Maximize:

\[
Q(\theta, \theta_{p-1}) = E \left[ \log f(y \mid x, \theta) \mid Y, \theta_{p-1} \right]
+ E \left[ \log p(x \mid \theta) \mid Y, \theta_{p-1} \right]
\]

Maximization Step:
- Performs max over X
- Also generates estimated probabilities per pixel (length of time in state k) to pass back to E-step
  - Estimate of:
  - This strategy is robust for MPM, but is a weak estimate for MAP-ICM and MAP-SA

\[
p_{x_s \mid y}(k \mid y, \theta(p-1))
\]
EM Update Equations

Equations estimating Mean, Variance and Number of pixels for each class

\[
\mu_k(p) = \frac{1}{N_k(p)} \sum_{s \in S} y_s p_{X_s | Y}(k | y, \theta(p-1))
\]

\[
\sigma_k^2(p) = \frac{1}{N_k(p)} \sum_{s \in S} (y_s - \mu_k(p))^2 p_{X_s | Y}(k | y, \theta(p-1))
\]

\[
\mu_k(p) = \frac{1}{N_k(p)} \sum_{s \in S} p_{X_s | Y}(k | y, \theta(p-1))
\]
Class Label Optimization

● Similar to Automatic Selection of # of Classes, EM step:
  ● Figueiredo, Jain; PAMI 2002

● We use simple subset:
  ● Merge classes if number of pixels are smaller than threshold
  ● Merge classes if means are closer than a threshold
  ● Example, starting with N=10 below: (p is EM iteration #)

\[
\begin{align*}
\text{p}=0 & \quad \text{p}=1 & \quad \text{p}=2 & \quad \text{p}=5 & \quad \text{p}=10 \\
\end{align*}
\]

Lauren Christopher, PhD
Initialization

- How to initialize \( \theta \)? It makes a big difference!
- Example, SNR=0.5 (N=4), two MPM initializations:

\[
\theta = (10,4.5,90,4.5,180,4.5,250,4.5) \quad \theta = (50,4.5,67,4.5,180,4.5,250,4.5)
\]
Initialization

- Some references use ML estimates as initialization
  - Dubes et. al. [1990 Conf. On Pattern Recognition]
  - Disadvantage: class means close together in low SNR
- We estimate mean and variance, and then evenly distribute class means from $-3\sigma$ to $+3\sigma$ evenly, with

$$\sigma_k = \frac{6\sigma}{N}$$
2D Ultrasound: Variable Mean

- Tumor and Background classes mixed in segmentation
  - Due to attenuation in ultrasound
- Some recent research (MAP-MPM): (Marroquin; 2002)
- We Vary the Mean of the Gaussian over the Image
  - Difference – used inside EM Update Equations
    \[ \mu_k(p) = m_k^*(p)s + b_k^*(p) \]
  - Solve the MMSE equations with posterior estimates
    \[
    \begin{bmatrix}
    m_k^*(p) \\
    b_k^*(p)
    \end{bmatrix}
    = \begin{bmatrix}
    A^T \cdot A & A^T
    \end{bmatrix}^{-1} \begin{bmatrix}
    y_s P_{X_s|Y} \\
    \vdots \\
    \vdots \\
    y_s P_{X_s|Y}
    \end{bmatrix}
    \]
Some other images: CT Scan
Some other images: Me
Some other images: Einstein